Modeling and Optimization of Material Removal Rate Based on Artificial Intelligence in Electrical Discharge Machining Using Super Alloy

Ranjeet Singh Thakur[1], Dr. Shrihar Pandey[2*], Shiwangi Mishra[3], Babli Lodhi[4], Akash Mishra[5]

[1, 3]Research Scholar, Mechanical Engineering Department, Eklavya University Damoh (M.P.)
[2*]Associate Professor and Head, Mechanical Engineering Department, Eklavya University, Damoh (M.P.)
[4, 5]Assistant Professor, Mechanical Engineering Department, Eklavya University, Damoh (M.P.)

***CorrespondingAuthor:** Dr. Shrihar Pandey
*Associate Professor & Head
Email id: shriharpandey@gmail.com

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Abstract:
Because of its exceptional mechanical qualities, titanium superalloy is most commonly employed in aero planes, spacecraft, naval ships, missiles, and many other significant industries. The most effective production techniques for shaping these kinds of materials are unusual machining processes, or UMPs. One such thermal energy-based UMP that has gained widespread acceptance for the machining of titanium alloys is electrical discharge machining (EDM). In the current study, material removal rate (MRR) was assessed using EDM on Ti-6Al-4V alloy by adjusting peak current, pulse-on time, and pulse-off time. After developing an artificial neural network (ANN) model for MRR, a hybrid strategy combining ANN and genetic algorithms was used to optimise MRR for a single aim.

Keywords: Artificial Neural Network, EDM, Genetic Algorithm, Material Removal Rate, Optimization

1. Introduction

Superalloys belong to a relatively newer class of materials which have become very popular due to their enhanced mechanical and physical properties. Hastelloy, Inconel, Rene alloys, was paloy Incoloy etc. are few of examples of superalloys.Ti-6Al-4 Vissucha super alloy which is very popular in aviation and automobile industries. However, machining of this material is very difficult by conventional method. Unconventional machining processes (UMPs) are very popular to machine such materials. Many UMPs have been developed in past to process these materials. The most popular UMPs today are electrical discharge machining (EDM), ECM, LBM, PAM, AJM,USM etc. EDM is a thermal energy based UMP which utilizes the thermal energy of thespark generated betweenthe tool and the workpiece. The removal of the material takes place due to melting and or vaporization of workpiece due to localized intense heat [1-2].Researchers have done considerable amount of work using EDM during machining of Titanium alloys.Pramanik et al. [3] tried to improve the efficiency of wire EDM (WEDM) process by reducing the wire rupturеduring cutting of Ti-6Al-4V superalloy. Flushing pressure, wire tension and pulse-on time were considered as inputcontrol factors. They discussed various mode of wire fracture and also suggested that to reduce wire fracture, less tension, lower pulse-on time and higher flushing pressure should be used. Mustafa et al. [4] performed mirco-EDMon Ni-Ti memory shape alloy by using different electrode materials and by varying capacitance and discharge voltage. The output parameters were MRR, TWR, SR, hope taper, circularity and overcut. They concluded that capacitance and electrode material are dominant factors affecting performance of the process. They also identified the optimum control factors to minimize the TWR and SR by using MOGA-II. De et al. [5] machined pure sintered titanium by using WEDM. Pulse-on time, pulse-off time, wire tension and feed were varied to evaluate two of the most important output process parameters; kerf width and overcut. By using 4 factors- 3 level factorial design, they developed response surface models for kerf width and overcut and found models to be appropriate to predict the behavior of the process. Zhang et al. [6] performed magnetic field assisted EDM on Ti-6Al-4V superalloy byconsidering current, pulse-on time, pulse-off time and magnetic field intensity as input control factors. Apart from improving the MRR and TWR, they also aimed to improve the performance of the process by reducing the energy consumption and machining noise. They concluded that the present technology significantly improves the performance of EDM by reducing the electrode wear, energy consumption, carbon emissions, and machining noise.Jing et al. [7] attempted to address the issue of arcing during EDM of titanium alloy. They used multiple-input, multiple-output adaptive control system to reduce the arcing during the process. Arikatla et al. [8] carried outWEDM on Ti-6Al-4V alloy by considering pulse-on time, pulse-off time, servo voltage, wire tension and power asinput control factors. They developed empirical model for kerf width, MRR and SR by using response surface methodology. Wu et al.[9] investigated the effect of EDM on crater size, phase transformation in heat affected zoneand residual stress by using finite element method. They predicted crater size, phase transformation and residualstress for different discharge energy levels during the process. Kolli et al. [10] mixed surfactant and graphite powderin dielectric to improve the process performance of EDM during machining of Ti-6Al-4V superalloy. MRR, TWR,SR and recast layer thickness were considered as performance parameters. They concluded that discharge current and surfactant concentration are most significant control factors for MRR and TWR while discharge current and powder concentration are most significant for SR and recast layer thickness. Baroi et al. [11] carried out EDM onTitanium Grade 2 alloy to evaluate MRR, TWR and SR by using L16 orthogonal array design of experiments. They obtained optimum values of all the three quality parameter sby using Taguchi robust design method.

The available literature shows that people have studied the effects of different process parameters during EDM/WEDM of Titanium alloys to explore the various process performances. Also, few researchers have used conventional optimization techniques for modeling and optimization of the process. But modeling and optimizationusing artificial intelligence based approach requires further attention during EDM of Ti-6Al-4V. Keeping above in the mind in the present research the machining has been performed on Ti-6Al-4V by varying peak current, pulse-ontime and pulse-off time. One of the most important performance parameters; MRR has been evaluated. The artificial neural network (ANN) model in mathematical form has been developed for MRR. Further, a combined approach of ANN and genetic algorithm (GA) has been applied for optimization of MRR.

2.Methodology

Artificial Neural Network(ANN)

ANN is one of the tools of artificial intelligence, whose working is analogous to the brain. In ANN very largenumbers of neurons are interconnected and they propagate the information among themselves.ANN architecture consists of input layer, hidden layer and output layer. Apart from these layers, the weights and biases are also very important elements in ANN.The first signal (in terms of control factors) is given to input layer which processes these signals by considering weights and bias. Then it is processes by some activation function such as log-sigmoid,tangent-sigmoid, pure-linear etc. to give the output. The output from each neuron is forwarded to the neurons in the nextlayer and the process is repeated.At ypical ANN architecture is shown in the Fig. 1.

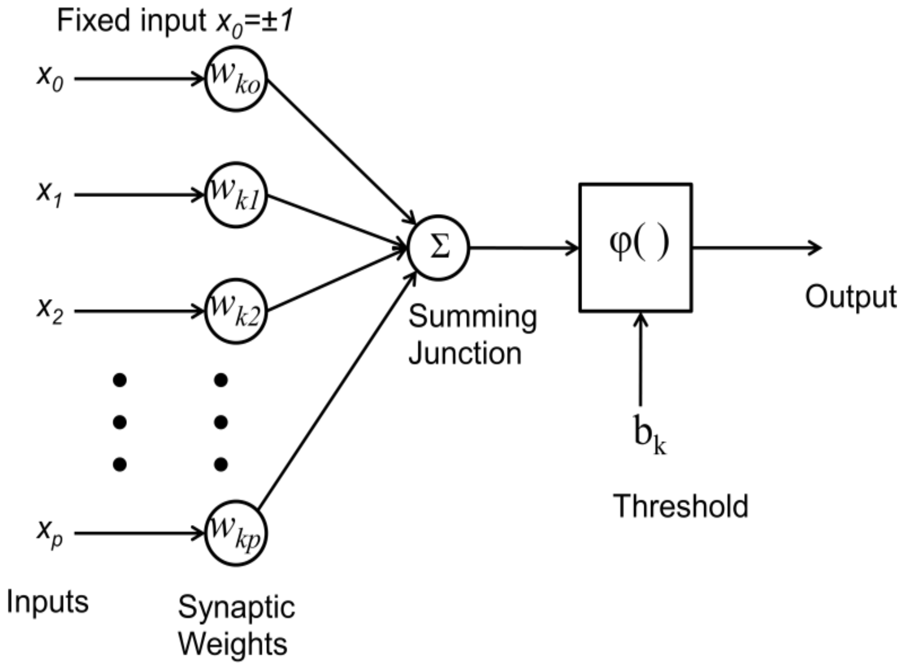

Fig.1 Architecture of artificial neral network

In feed forward back propagation fully connected ANN, each neuron in a layer is connected with all other neurons of previous layers and receive input from them. All the inputs to the neuron are summed up in the summation junction as mentioned below[12]:

$$net_p = \sum_{i=1}^{N} w_{kp} X_k + b_p \qquad (1)$$

Where $w_{kp}$is the weight of connection to pth neuron in a particular layer from preceding layer and b_p is the bias tothat particular neuron.N is the total number of inputs to pth neuron. X_k is the input from the neuron in the preceding layer to the forward layer. The output of summation junction is processed by some activation function (Ø) to give final output Y_p from the neuron as given below:

$$Y_p = \text{F}\ (net_p) \qquad (2)$$

Activation functions for a particular ANN are selected in such a way so as to minimize the mean square error (MSE) between experimental values and model predicted values.

Genetic Algorithm (GA)
GA is a metaheuristic which is based on the process of the natural selection. Normally it is used to solve nonlinear optimization problems where classical methods are slow or not able to give best results. GA starts with initialization of random population and then moves towards finding best or optimal solution through the process of selection, cross over and mutation. The population is checked with the objective function to identify the best individuals. The best fitness individuals are used to create new population through the process of cross-over andmutation. These new individuals are again checked for their fitness with respect to objective function and this cycle is repeated to satisfy some termination criteria [12].

2. Experimental details
The experiments were performed on CNC Electronica Smart die sinking electrical discharge machine as shown in the Fig. 2. The input control factors selected were peak current, pulse-on time and pulse-off time. The different input control factors and their levels are given in Table 1.

Fig.2 EDM Machine tool

Table1 Control Factors And Their Levels

Factors	Peak current(A)	Pulse-on time(μs)	Pulse-off time(μs)
Level	X_1	X_2	X_3
Low(-1)	5	50	25
Central(0)	7	75	50
High(1)	9	100	75

The positive polarity has been used during the experimentation as the Ti-6AI-4V has been selected work piece material. The experiments have been performed using box-behnken design of experiments .Each experiment was performed for 45 minutes and the response MRR in each experimental run are obtained by calculating the difference of mass of the work piece/tool measured before and after the experiment. The precision electronic digital weight balance with 0.1 mg resolution was used to measure the mass of the samples. The MRR in mg/min were calculated by following formula:

$$MRR= \frac{m_i - m_f}{\cdot tp3)} \qquad (3)$$

Where m_i and m_f are the initial & final mass of the work piece (after machining); respectively. The observed value of quality characteristic has been shown in Table 2.

Table2 Experimental Observation

Experiment No	Control factors			
	x1	x2	x3	MRR (mg/min)
1	0	0	0	0.64
2	-1	-1	0	0.58
3	0	0	0	0.65
4	-1	1	0	0.57
5	0	1	-1	0.71
6	0	1	1	0.74
7	1	1	0	0.88
8	1	-1	0	0.77
9	1	0	-1	0.76
10	0	0	0	0.64
11	-1	0	1	0.61
12	0	-1	-1	0.62
13	-1	0	-1	0.45
14	1	0	1	0.98
15	0	-1	1	0.69

3. Modeling and Optimization

Artificial Neural Network Model

In this research, after trying different activation functions and their combinations, it has been found that log sigmoid and pure linear activation function, for hidden layer and output layer, respectively, are best for all thequality characteristics. So, the log sigmoid and pure linear activation function has been utilized to develop ANN models.

The values of weights and biases, after network getting trained, have been used to develop the ANN model of MRR in mathematical form. The model with 5 neurons in the hidden layer has been found appropriate for MRR model. The ANN model in mathematical form can be expressed as:

$$MRR=0.18111*y_1+0.25081*y_2-0.3219*y_3-0.65823*y_4+0.63698*y_5+0.26168 \quad (4)$$

Where,

$$y_1 = \frac{1}{[1+e^{-(-3.3924*x_1-0.8639*x_2-1.4398*x_3+4.8762)}]}$$

$$y_2 = \frac{1}{[1+e^{--0.52686*x_1-0.0275*x_2+0.037796*x_3-2.4171)}]}$$

$$y_3 = \frac{1}{[1+e^{-(-1.428*x_1+4.2696*x_2+3.5469*x_3-0.1161)}]}$$

$$y_4 = \frac{1}{[1+e^{-(-1.428*x_1+4.2696*x_2+3.5469*x_3-2.418)}]}$$

$$y_5 = \frac{1}{[1+e^{-(-1.428*x_1+4.2696*x_2+3.5469*x_3-4.7439)}]}$$

Fig. 3 compares the experimental values of MRR with the models predicted values. The MSE is a yard stick to measure the model accuracy. The MSE for MRR by ANN model has been found to be 1.12×10^{-5}, which are almost negligible. So, it can be concluded here that model is capable enough to predict MRR.

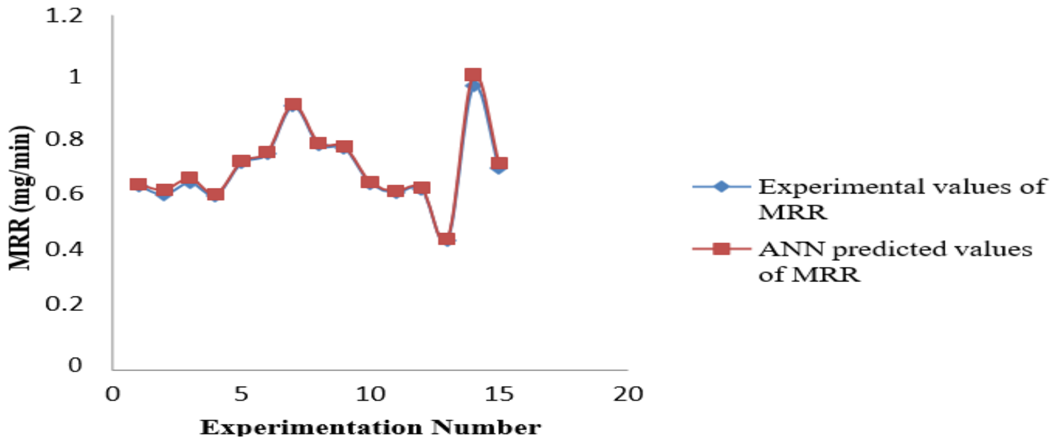

Fig.3 Comparison of model predicted values with experimental values for MRR

Optimization using GA

Fig.4 shows the flow chart for ANN-GA hybrid approach during modeling and optimization of the process in the present case, the objective function of optimization problem can be stated as below:

Find :x_1, x_2 and x_3

Maximize:

$$MRR=0.18111*y_1+0.25081*y_2-0.3219*y_3-0.65823*y_4+0.63698*y_5+0.26168 \quad (5)$$

With range of process input parameters: $5\leq x_1\leq 9$

$50\leq x_2\leq 100$

$25\leq x_3\leq 75$

The critical parameters of GA are the size of the population, mutation rate, cross-over rate and number of generations. After trying different combinations of GA parameters, the population size 50, cross-over rate 0.8, mutation rate 0.05 and number of generation 110 have been taken for MRR. The objective function in Eq. (5) has been solved without any constraint. In Fig. 5, the best and mean fitness curves are illustrated in the search space.The fitness function is optimizedwhen the mean curve converges to the best curve after 20 generation. The corresponding values of control factors peak current, pulse-on time and pulse-off time have been identified as 9 A,50 µs and 75. Hence these are the optimum values of control factors. Using these values, the value of MRR has been obtained as1.102 mg/min.

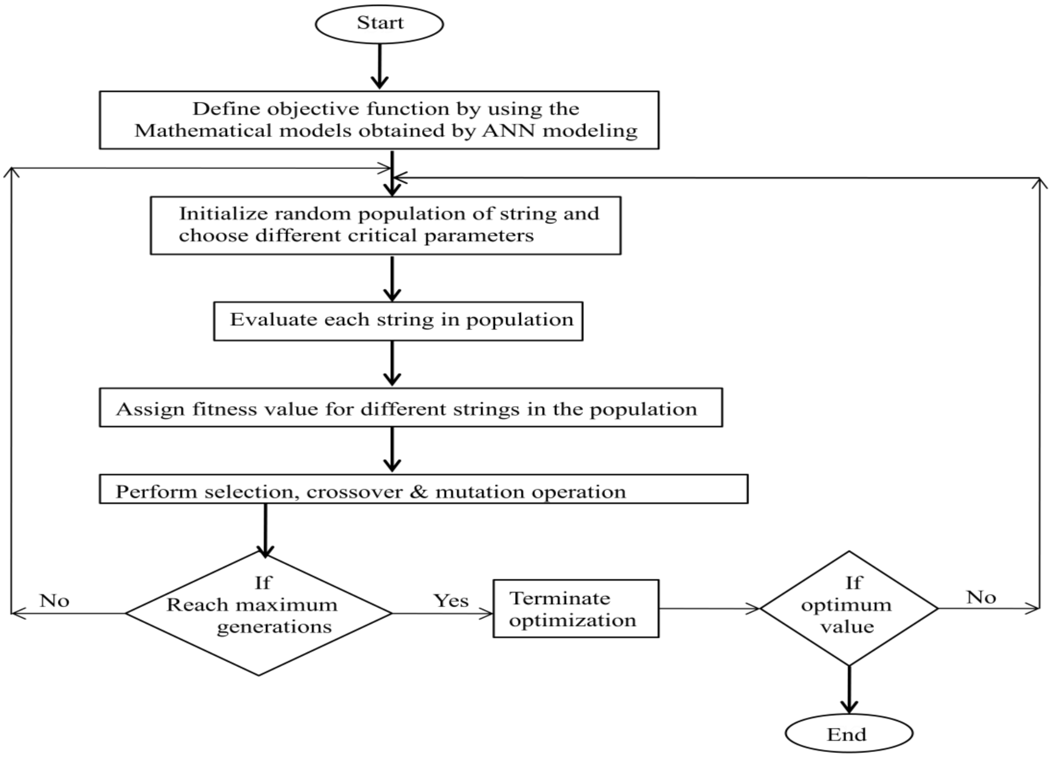

Fig.4 ANN-GA hybrid approach

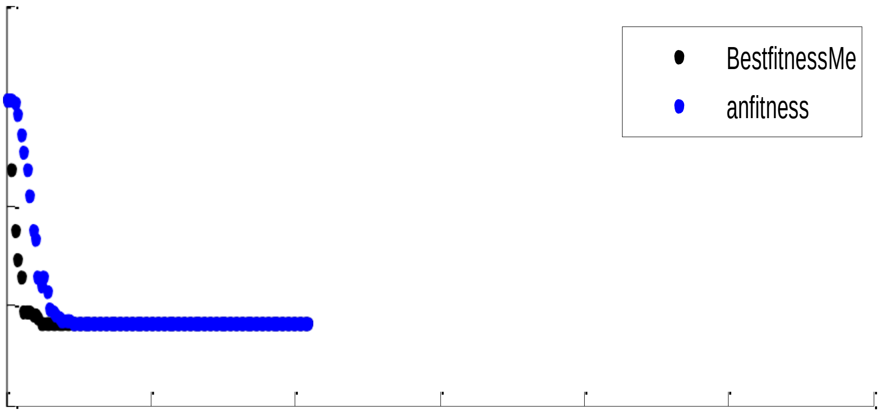

Fig.5 Generation-fitnessgraphicsforMRR

The confirmation experiment has also been performed at predicted optimum level of control factors andshown in Table 3. The comparison of optimum result with that of results obtained at initial level of control factors shows considerable improvement of 74% in MRR.

Table3 Optimization and confirmation results for MRR

	Initial process parameters	Optimal process parameters		Increment(%)
		Prediction	Experiment	
Peak current (A)	7.0	9	9	-
Pulse-on time (µs)	75	50	50	-
Pulse-off time (µs)	50	75	75	-
MRR (mg/min)	0.61	1.2	1.1	73

4. Conclusions:

Following conclusions can be drawn from the present research:

1. Electrical discharge machining is a feasible process to machine advanced materials such as super alloys.
2. The artificial neural network (ANN) is best modeling tool when process behavior is non-linear. As the developed model with negligible prediction error are accure at and reliable.
3. Hybrid approach of ANN and genetic algorithms hows the considerable improvement of 74% in material removal rate.

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